Collaborative Detection with Uncertain Signal Distributions in Wireless Sensor Networks

Tai-Lin Chin, Jiun-Hao Chen and Cheng-Chia Huang
Department of Computer Science and Information Engineering
National Taiwan University of Science and Technology
Taipei, Taiwan 106
Email: tchin@mail.ntust.edu.tw

***Abstract*—Sensor networks are envisioned to have the capability to detect the presence of an event or target in a monitored region. Sensors can collect measurements about the target and make local decisions about the presence or absence of the target. To reduce probability of false alarms, collaborative detection is usually exploited, where the local decisions are fused to arrive at a consensus about the target presence. In general, the performance of a sensor network can be evaluated in terms of detection probability and false alarm probability. This paper adopts the Constant False Alarm Rate (CFAR) detector for sensors to make local decisions. The distributions of the target signal and noise are assumed unknown a priori. Simple and effective methods are proposed to estimate the distributions of sensor measurements. The AND and OR fusion methods are exploited in making the final decisions. Simulations are conducted to verify the analytic results to the simulated results. The best selection of sensors to participate the fusion in order to protect a particular location in the monitored region is also shown by experiments. Essentially, the paper analyzes the approximated detection probability and false alarm probability based on the estimated distributions of the unknown target signal and noise. Through simulations, it is shown that those approximated results could be close to the true values.**

Keywords–Sensor networks; Target Detection; Data Fusion; Constant False Alarm Rate.

I. INTRODUCTION

The advances of technologies in sensor networks have made it possible to improve the capability of human to monitor a region of interest. One potential application of sensor networks is to detect the presence of abnormal events or targets in the monitored region. For instance, sensor networks have been used in battlefield monitoring in order to detect unauthorized intrusions[1], [2], or in wildfire detection to protect forests[3]. In such networks, sensors deployed in the monitored region can sample the environment, exchange information with other sensors, and make decisions about the presence or absence of the events or targets. In many cases, the targets may be dangerous or malicious. Consequently, to design effective and reliable detection methods is an important issue for such applications in sensor networks.

Many studies use data fusion to improve detection performance in sensor networks[4], [5], [6], [7]. In most of the studies, sensors are usually used to detect certain signals for which the probabilistic distributions are assumed to be known. However, in practice, the distributions of the target signal and noise might not be known in advance. Furthermore, the distributions could change from time to time caused by the unpredictable and variant physical environment conditions.

This paper considers the problem of detecting a target with unknown signal distribution in sensor networks. Basically, sensors take samples of the target signal and measure the average signal energy periodically. In each period, a local decision about the presence or absence of the target is made by each sensor using Constant False Alarm Rate (CFAR) detector. If the measurements is greater than a carefully selected threshold, it decides that a target is present. Otherwise, it decides that no target is present. An appropriate threshold depends on the distributions of the measurements in both cases when the target is present and absent. A simple and effective method is proposed to estimate the probabilistic distributions of the target signal and the noise. Without complicated calculations, approximate distributions of the measurements are estimated. Moreover, data fusion is also used to further improve the performance of the network. A consensus decision is arrived at a fusion center periodically based on the local decisions reported from sensors. Two fusion methods, namely AND-fusion and OR-fusion, are investigated for data fusion in the network. In particular, the global detection performance in terms of detection probability subject to a fixed false alarm probability is derived analytically based on the estimated distributions.

Simulations are conducted to verify the correctness of the analytic derivations of the detection performance. The comparisons show that the analytic results are very close to the simulation results. The discrepancy between the analytic results and simulation results is mainly caused by the approximations of the signal distributions. In addition, it can be found that not all sensors need to participate in the fusion. In fact, the detection performance may decrease as the number of sensors increases in the fusion. However, if too few sensors in the fusion, it is not beneficial to target detection, either. The best set of sensors to participate in the fusion for a certain target location is also selected by simulations for both AND and OR fusion. The selection can be the basis to generate an efficient and high-performance surveillance sensor network.

The rest of the paper is organized as follows. Section II reviews the related work. Section III addresses the detection mechanism and the analytic derivations of the detection performance. Section IV shows the simulation results. The paper concludes in Section V.

II. RELATED WORK

Target detection using sensor networks has been extensively studied in the literature. A variety of detection methods have been proposed for target detection in sensor networks[8],

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[9]. Some studies in the literature assume that the sensing range of a sensor is a disc[10]. A sensor will report a positive decision if the target is present within its sensing range. However, this model may not conform to real situations since it does not capture the stochastic nature of sensing data. Detection errors like false alarm and missing of target's presence may occur from time to time in real detection operations. Some other studies use different probabilistic models to catch the uncertain characteristics of detection operations in sensor networks[11], [12]. In general, the detection probability is usually assumed to be degraded with the distance from the target to the sensor. Based on the assumption, in [11], the coverage of a location in the monitored region is defined as the probability that at least one sensor detects the target if it is present at the monitored location. A sensor deployment strategy is proposed to achieve that the minimal coverage over the region is greater than a threshold. In [12], the detection probability of a mobile target is analytically evaluated when a group of sensors deployed in the monitored region. A probabilistic detection model where each sensor can have heterogeneous sensing area is developed.

In order to improve detection performance, data fusion is usually used to reduce the probability of false alarm or missing[4], [5], [6], [7]. In [4], the monitored region is divided into a grid and two data fusion methods applying to the grid are investigated. One uses data reported from an individual cell and the other uses data from adjacent cells. The latter is shown to be able to generate better performance for the coverage. In [5], the lower and upper bounds of fusion threshold is analytically derived to ensure that a higher detection probability and lower false alarm probability can be obtained compared to those derived from the weighted averages of individual sensors. In [6], the paper investigates collaborative target detection based on data fusion. The optimal detector, which is proven to be uniformly most powerful, is derived. In [7] and [13], the latency of detecting a target based on data fusion in sensor networks is also analyzed. Detection latency is an important issue for real time detection. Recently, there is also work on the problem of target detection in mobile sensor networks [14], [15]. All of the above studies use data fusion, but derives the detection mechanism based on known signal or noise distributions. Our work is different from those previous studies in that the distributions of the target signal and noise are not necessary to be known in advance, which could be much closer to real situations.

III. DETECTION

A. Sensing Model

Suppose that a target at location r emits a signal S_t at time t. The distribution of S_t is unknown, but the mean and variance of S_t are easy to evaluate. Let μ_s and σ_s^2 denote the mean and variance of S_t. Let S_t^i be the signal sensed by sensor i at location r_i. The signal strength is assumed to be degraded with distance. Thus, S_t^i can be modeled as follows:

$$S_t^i = \frac{S_t}{|r - r_i|^{\alpha}}, \tag{1}$$

where $|r - r_i|$ is the Euclidean distance from the target to sensor i and α is the decay factor. Note that since $|r - r_i|^{\alpha}$ is a constant, the mean and variance of S_t^i are given as follows:

$$\mu_{s,i} = \frac{\mu_s}{d_i} \text{ and } \sigma_{s,i}^2 = \frac{\sigma_s^2}{d_i^2}, \tag{2}$$

where $d_i = |r - r_i|^{\alpha}$. Usually, the signal sensed by a sensor is corrupted by noise. Let X_t^i denote the noise signal at sensor i, and is modeled as a random variable with mean $\mu_{x,i}$ and variance $\sigma_{x,i}^2$. Noise can follow a variety of distributions in different environment conditions. In this paper, the distribution of X_t^i is also assumed to be unknown. The final signal sensed by sensor i is $y_t^i = S_t^i + X_t^i$.

Generally, each sensor in the network measures the average signal energy over a sampling period. The measurement of a sensor can be expressed as

$$M_i = \frac{1}{T}\sum_{t=1}^{T} \left|y_t^i\right|^2 = \frac{1}{T}\sum_{t=1}^{T} \left|S_t^i + X_t^i\right|^2, \tag{3}$$

where T is the number of samples in one period.

B. Approximation of Measurement Distributions

In each sampling period, each sensor would make a local decision based on its measurements. Assume that the sampling result at each time instant is independent. The distribution of the measurement M_i can be approximated by Central Limit Theorem (CLT). When the target is absent, the measurement contains only noise, i.e.,

$$M_i = \frac{1}{T}\sum_{t=1}^{T} \left|X_t^i\right|^2. \tag{4}$$

Suppose X_t^i is an independent identically distributed (i.i.d.) random variable. First, the distribution of ${X_t^i}^2$ is determined. In order to apply CLT, the mean and variance of ${X_t^i}^2$ need to be determined. It is easy to get $E[|X_t^i|^2] = \mu_{x,i}^2 + \sigma_{x,i}^2$. However, there is no closed form expression for the variance of $|X_t^i|^2$. To solve the problem, "Delta Method", which finds the approximation of a function of a random variable is exploited. Delta Method is described as follows.

Proposition 1: Let x be a random variable with mean μ and variance σ^2. The variance of a function $f(x)$ can be approximated by

$$Var(f(x)) \approx [f'(\mu)]^2 \times \sigma^2.$$

Proof: The Taylor series expansion of a function $f(\cdot)$ at value a is given by

$$f(x) = f(a) + f'(a)(x-a) + f''(a)\frac{(x-a)^2}{2!} + \cdots.$$

Take the first two terms as an approximation and let $a = \mu$,

$$f(x) \approx f(\mu) + f'(\mu)(x - \mu).$$

Take the variance of both sides, one can have

$$Var(f(x)) \approx [f'(\mu)]^2 \times Var(x).$$

■

Let $f(X_t^i) = {X_t^i}^2$. From Proposition 1, the variance of ${X_t^i}^2$ can be approximated by $4\mu_{x,i}^2\sigma_{x,i}^2$. Using the approximation as the variance and the mean of ${X_t^i}^2$ obtained previously, by CLT, when T is large, M_i converges in distribution to a Gaussian distribution $N(\mu_{i,0}, \sigma_{i,0}^2)$, where

$$\mu_{i,0} = \mu_{x,i}^2 + \sigma_{x,i}^2 \text{ and } \sigma_{i,0}^2 = 4\mu_{x,i}^2\sigma_{x,i}^2/T. \tag{5}$$

Note that the mean $\mu_{i,0}$ is accurate, but the variance $\sigma_{i,0}^2$ is approximated based on Proposition 1.

The approximated distribution of M_i when the target is present can also be derived in a similar way. If the target is present, sensor measurements are mixed by target signal and noise as in (3), which can be rewritten as follows:

$$M_i = \frac{1}{T}\sum_{t=1}^{T}\left|S_t^i\right|^2 + \frac{1}{T}\sum_{t=1}^{T}\left|X_t^i\right|^2 + \frac{2}{T}\sum_{t=1}^{T}\left|S_t^i X_t^i\right| \quad (6)$$

Similar to the target absence case, using CLT and Proposition 1, the distributions of the first two terms in (6) can be approximated by the following two Gaussian distributions.

$$\frac{1}{T}\sum_{t=1}^{T}\left|S_t^i\right|^2 \sim N\left(\mu_{s,i}^2 + \sigma_{s,i}^2, \frac{4}{T}\mu_{s,i}^2\sigma_{s,i}^2\right) \quad (7)$$

$$\frac{1}{T}\sum_{t=1}^{T}\left|X_t^i\right|^2 \sim N\left(\mu_{x,i}^2 + \sigma_{x,i}^2, \frac{4}{T}\mu_{x,i}^2\sigma_{x,i}^2\right) \quad (8)$$

For the third term, assume that target signal and noise are independent, one can also get the mean and variance of $S_t^i X_t^i$ as follows:

$$E\left[S_t^i X_t^i\right] = E\left[S_t^i\right]E\left[X_t^i\right] = \mu_{s,i}\mu_{x,i}$$

$$\begin{aligned} Var\left(S_t^i X_t^i\right) &= E\left[\left(S_t^i X_t^i - \mu_{s,i}\mu_{x,i}\right)^2\right] && (9)\\ &= E\left[S_t^{i2}\right]E\left[X_t^{i2}\right] - \mu_{s,i}^2\mu_{x,i}^2 && (10)\\ &= \mu_{s,i}^2\sigma_{x,i}^2 + \mu_{x,i}^2\sigma_{s,i}^2 + \sigma_{s,i}^2\sigma_{x,i}^2 && (11) \end{aligned}$$

Again, by CTL, when T is large, the distribution of the third term in (6) can be approximated by a Gaussian distribution as follows.

$$\frac{2}{T}\sum_{t=1}^{T} S_t^i X_t^i \sim N\left(2\mu_{s,i}\mu_{x,i}, \frac{4}{T}\left(\mu_{s,i}^2\sigma_{x,i}^2 + \mu_{x,i}^2\sigma_{s,i}^2 + \sigma_{s,i}^2\sigma_{x,i}^2\right)\right) \quad (12)$$

Obviously, the distribution of measurement M_i when the target is present can be approximated by adding the three Gaussian distribution in (7), (8) and (12). Therefore, when the target is present, M_i can also be approximated by a Gaussian distribution $M_i \sim N(\mu_{i,1}, \sigma_{i,1}^2)$, where

$$\mu_{i,1} = \sigma_{s,i}^2 + \sigma_{x,i}^2 + \left(\mu_{s,i} + \mu_{x,i}\right)^2, \quad (13)$$

and

$$\sigma_{i,1}^2 = \frac{4}{T}\left(\mu_{s,i}^2 + \mu_{x,i}^2\right)\left(\sigma_{s,i}^2 + \sigma_{x,i}^2\right) + \sigma_{s,i}^2\sigma_{x,i}^2. \quad (14)$$

Again, the mean $\mu_{i,1}$ is accurate, but the variance $\sigma_{i,1}^2$ is approximated based on Proposition 1.

C. Local Detection

With the distributions of sensor measurements, it is possible to control the performance of the detection operations. By the detection procedure, sensors would collect measurements and make a local decision about the presence or absence of the target. A potential method to make the decision is the CFAR detector as shown in Figure 1. Essentially, the detector compares the signal energy measurement, M_i, to a threshold, η_i. If the measurement is greater than the threshold, the detector reports a positive detection. Otherwise, it reports a negative detection. The false alarm probability is defined as the probability that the detector makes a positive decision (i.e., the target is present) when the target is actually absent.

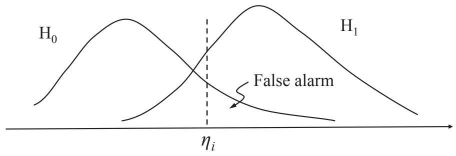

Figure 1. Constant false alarm rate detection

From the previous derivations, the approximate distributions of measurements when the target is present and when the target is absent are known. The detection threshold η_i can be determined subject to a false alarm probability constraint. Specifically, let H_0 be the null hypothesis for the condition that the target is absent and H_1 be the alternative hypothesis for the condition that the target is present. When the target is actually absent, since M_i conforms to a Gaussian $N(\mu_{x,i}^2 + \sigma_{x,i}^2, \frac{4}{T}\mu_{x,i}^2\sigma_{x,i}^2)$, the false alarm probability is given by

$$\begin{aligned} P_{f,i} &= P(M_i > \eta_i \,|H_0\,) && (15)\\ &= Q\left(\frac{\eta_i - \mu_{i,0}}{\sigma_{i,0}}\right), && (16) \end{aligned}$$

where $\mu_{i,0}$ and $\sigma_{i,0}$ are from (5), and $Q(x)$ is the tail probability of a standard normal distribution, i.e.,

$$Q\left(x\right) = \frac{1}{\sqrt{2\pi}}\int_x^{\infty}\exp\left(-\frac{u^2}{2}\right)du.$$

Thus, given a tolerable false alarm probability, one can determine the threshold η_i for the detection operation.

Furthermore, given the target is present, M_i conforms to $N(\mu_{i,1}, \sigma_{i,1})$. Detection probability is defined as the probability that the detector decides a target is present while there is a target present. Therefore, the detection probability can be derived as

$$\begin{aligned} P_{d,i} &= P(M_i > \eta_i \,|H_1\,) && (17)\\ &= Q\left(\frac{\eta_i - \mu_{i,1}}{\sigma_{i,1}}\right), && (18) \end{aligned}$$

where $\mu_{i,1}$ and $\sigma_{i,1}$ are from (13) and (14).

D. Fusion

To further reduce potential false alarms, local decisions of sensors are sent to a fusion center where a consensus decision about the presence or absence of the target is made. Two common used fusion methods are AND fusion and OR fusion. For the AND fusion, the fusion center decides that a target is present if all sensors participating the fusion report positive local decisions. Otherwise, it decides that no target is present. Therefore, the false alarm probability of the final consensus is the probability that all sensors report positive local decisions when there is no target present, i.e.,

$$P_f = \prod_{i=1}^{n} P_{f,i}. \quad (19)$$

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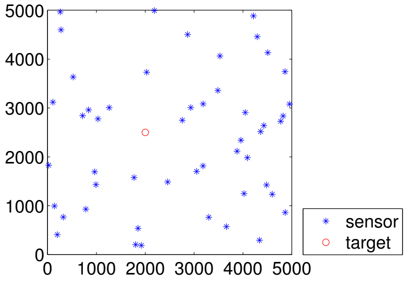

Figure 2. Sensor deployment

In contrast, the detection probability of the final consensus is the probability that all sensors report positive local decisions when a target is present indeed, i.e.,

$$P_d = \prod_{i=1}^{n} P_{d,i}. \tag{20}$$

Similarly, for the OR fusion, the fusion center decides that a target is present if at least one sensor participating the fusion reports a positive local decision. Otherwise, it decides that no target is present. Therefore, the final false alarm probability and detection probability can be derived as in (21) and (22), respectively.

$$P_f = 1 - \prod_{i=1}^{n} (1 - P_{f,i}) \tag{21}$$

$$P_d = 1 - \prod_{i=1}^{n} (1 - P_{d,i}) \tag{22}$$

IV. Simulations

In the simulations, a sensor network is deployed in a 5000 meter × 5000 meter field. There are 50 sensors deployed in the field randomly as shown in Figure 2. The target is assumed to be at location (2000, 2500) if it is present. The signal of the target is assumed to be a random variable with mean 50000 and variance 3. The signal decays with distance and the decay factor is $\alpha = 2$. Without loss of generality, a Gaussian random process is used to generate the target signal. It is noted that any other random process can be used without affecting the correctness of the proposed method. The noise process at each individual sensor is also assumed to be Gaussian with mean between 1 to 3 and variance between 0 to 1.

The distribution of the measurement M_i is first evaluated. Sensor measurement M_i is the average of signal energy taken during a sampling period as shown in (3). The mean and variance of M_i when the target is absent are derived in (5) and when the target is present in (13) and (14), respectively. The mean in (5) and (13) are accurate, but the variance in (5) and (14) are estimated by Proposition 1. However, since the target signal and noise signal are assumed to be Gaussian, the true variance of M_i can also be derived as follows. Let x be a Gaussian random variable with mean μ_x and variance σ_x^2. Assume that

$$y = \left(\frac{x - \mu_x}{\sigma_x} \right).$$

TABLE I. Measurement statistic characteristics of a node at (1031.713, 2778.091)

H_0	Mean		Variance		
T	Simulation	True	Simulation	Estimation	True
30	1.313263	1.317921	0.015507	0.014908	0.015462
300	1.318351	1.317921	0.001414	0.001491	0.001546
800	1.317386	1.317921	0.000546	0.000559	0.000580
H_1	Mean		Variance		
T	Simulation	True	Simulation	Estimation	True
30	1.424624	1.429481	0.016872	0.014938	0.016818
300	1.429922	1.429481	0.001537	0.001494	0.001682
800	1.428929	1.429481	0.000595	0.000560	0.000631

Taking the square of both sides of the equality, one can have

$$\sigma_x^2 y^2 = x^2 - 2\mu_x x + \mu_x^2.$$

Therefore,

$$Var(x^2) = Var(\sigma_x^2 y^2) + Var(2\mu_x x).$$

Note that y is a standard Gaussian random variable and y^2 is a Chi-square random variable with one degree of freedom. Thus, y^2 has mean 1 and variance 2. Then,

$$Var(x^2) = 2\sigma_x^4 + 4\mu_x^2\sigma_x^2.$$

Finally, the variance of $\frac{1}{T}\sum_{t=1}^{T} x^2$ is

$$\frac{1}{T}\left(2\sigma_x^4 + 4\mu_x^2\sigma_x^2\right).$$

Consequently, let x be the random variable for noise, the variance of measurement M_i when the target is absent can be derived. Analogously, let x be the random variable for target signal plus noise, the variance of measurements when target is present can be obtained.

One sensor located at (1031.713, 2778.091) is chosen to investigate the statistics of its measurements. The target signal at the sensor is a Gaussian random variable with mean 0.05 and standard deviation 0.000003, and the noise is assumed to be Gaussian with mean 1.1 and standard deviation 0.3. The true mean and variance of the measurement are derived and shown in Table I. The approximated variance estimated based on Proposition 1 is also shown in the table. The results of the estimated variance are pretty close to the true variance. The histograms of the measurements are shown in Figure 3. From the figures, when the number of samples T is small, the measurement distributions for target absence and target presence overlap in quite a lot area. It implies that it would be more difficult for the sensor to tell whether the target is present or absent. In contrast, when T is large, the distributions are more concentrated and separated in two groups. Obviously, it is easier for the sensor to tell whether the target is present. Therefore, based on a fixed local false alarm probability, the local detection probability would be higher if T is large.

Figures 4 and 5 show the Receiver Operating Characteristic (ROC) curves for the AND fusion and OR fusion. In each figure, the figure shows global false alarm probability versus global detection probability. In order to get a proper threshold for each sensor such that the fixed global false alarm probability is sustained, the local false alarm probability for AND fusion and OR fusion is choosen as in (23) and (24), respectively.

$$P_{f,i} = \sqrt[n]{P_f} \tag{23}$$

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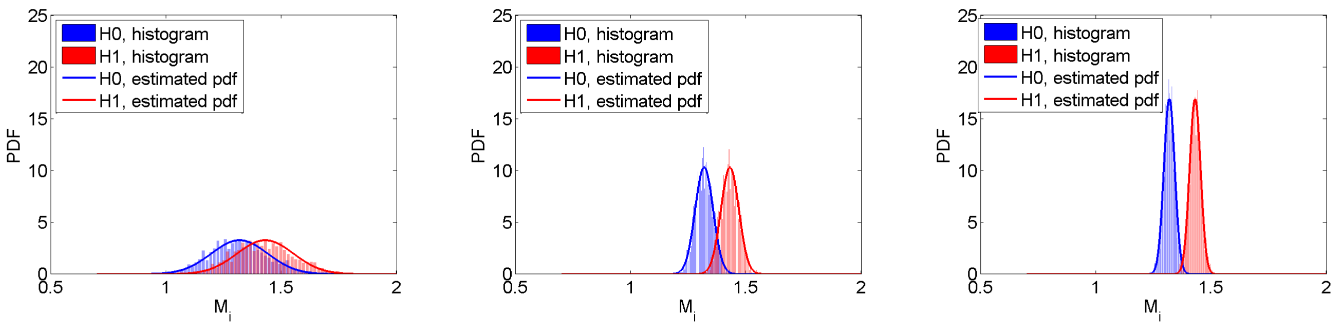

(a) T=30 (b) T=300 (c) T=800

Figure 3. The histograms of sensor measurements

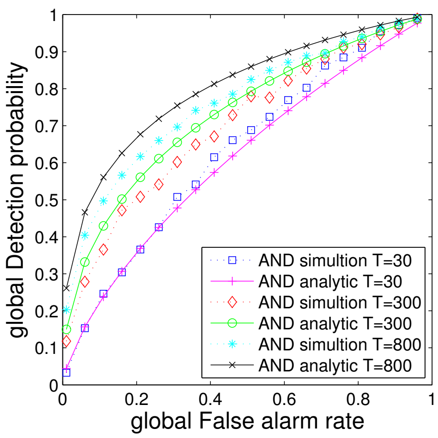

Figure 4. The ROC curves of the AND fusion

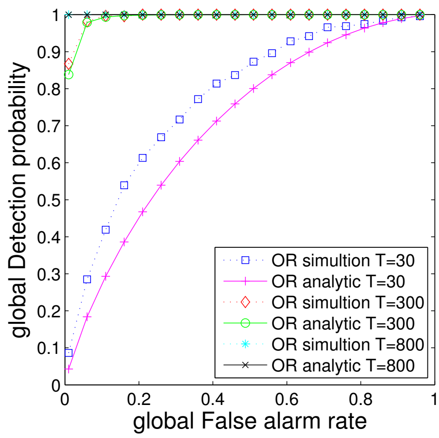

Figure 5. The ROC curves of the OR fusion

$$P_{f,i} = 1 - \sqrt[n]{1 - P_f} \tag{24}$$

Note that local false alarm probability for different sensors can be different for a fixed global false alarm probability. For the sake of simplicity, local false alarm probability of all the sensors are set to be identical. Given the false alarm probability, the detection threshold η_i for each sensor can be determined.

For the AND fusion shown in Figure 4, the analytic results are pretty close to the simulated results. The discrepancy between the simulated and analytic results primarily because the approximations made by CLT and the evaluations of the variance based on Delta method. In general, the system has higher detection probability if it can tolerate higher false alarm probability. In addition, when the number of samples T is large, the detection probability is higher. This is because local detection probability is higher if T is larger, and, thus, from (20), the global detection probability would be higher.

Similar results can be found in the OR fusion shown in Figure 5. Comparing the results of the AND fusion and OR fusion, the detection probability is higher for the OR fusion based on a fixed global false alarm probability. Obviously, the AND fusion requires all the sensors to report a positive detect decision in order to arrive at a positive consensus, while the OR fusion only requires at least one sensor reports a positive decision. The performance of the AND fusion may be degraded by the strict detection rule.

Figure 6 shows the number of sensors participating in the fusion versus the global detection probability using AND fusion. The sensors are ordered by signal to noise ratio, which is defined as the mean of the target signal over the mean of noise signal, i.e., $SNR = \mu_{s,i}/\mu_{x,i}$. The sensors are added to the fusion from the one with the highest SNR. In general, the sensors are added to the fusion roughly in the order of distance from the target location. From the result, it is obvious to see that using all sensors in the fusion is not the best choice. In fact, the detection probability decreases as the number of sensors increases after using three sensors in the fusion. On the other hand, if less than three sensors participate in the fusion, the detection performance also decreases. Consequently, from the simulations, the best choice for data fusion for the specified target location shown in Figure 2 is to choose the three sensors with the highest SNR. Similarly, for the other locations, one can also find the best sets of sensors to monitor the corresponding locations. The results could generate an efficient and high-performance strategy for monitoring the region of interest.

Figure 7 shows the results of similar experiments for

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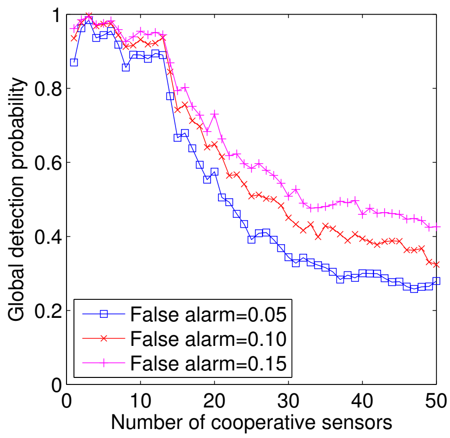

Figure 6. The impact of number of cooperative sensors for AND fusion

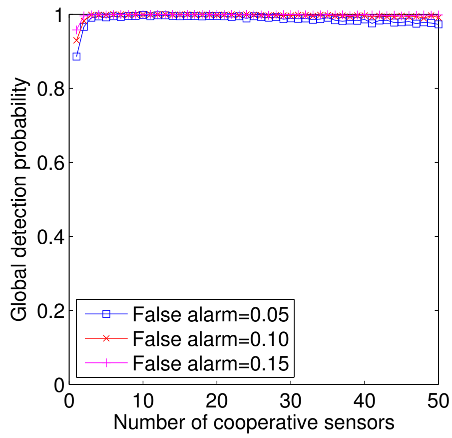

Figure 7. The impact of number of cooperative sensors for OR fusion

the number of participating sensors except using OR fusion. As shown in the figure, the system has highest detection performance when the three sensors with the highest SNR participates in the fusion. Either too many sensors or too few sensors participating in the fusion are not beneficial to the detection performance. It is consistent with the results in AND fusion. Although, in OR fusion, getting more sensors in the fusion would not hurt the performance much, using fewer sensors to monitor the region is always desired.

V. Conclusion

This paper investigates collaborative detection for a target in sensor networks when the distributions of the target signal and noise are unknown. A simple method is proposed to evaluate the approximations of the distributions of the sensor measurements. Using the approximated distributions, local detection decision thresholds can be derived for sensors based on CFAR detection. The global consensus decisions are made by the AND fusion and OR fusion rules. The detection performance in terms of the detection probability subject to a fixed false alarm probability is derived. The performance of both the fusion methods is verified by simulations. From the results, the analytic results are very close to the simulated results. In addition, the best set of sensors to participate in the fusion for monitoring a particular target location is also obtained by simulations. Selecting the best sets of sensors to monitor potential target locations in the region of interest can generate an efficient and high-performance surveillance sensor network.

This paper only investigates the AND and OR fusion rules. From the results, the OR fusion out performs the AND fusion in terms of detection probability subject to a fixed false alarm probability. However, these fusion methods may not be optimal in certain circumstances. For the future work, developing better fusion methods is worth to be explored.

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